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Outline

1. Introduction to Subgradients

2. Visualizing Subgradients

Challenge: What happens when we can't compute gradients?

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Common Examples in ML

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Solution: Subgradients

Subgradients generalize gradients to convex but non-differentiable functions

Key Insight: Even when derivatives don't exist, we can still do optimization!

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What is a Subgradient?

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$$f(x) \ge f(x_0) + g^{\mathsf{T}}(x - x_0) \quad \forall x$$

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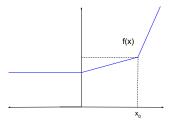
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Intuition: g defines a linear lower bound that touches f at x_0

The Classic Example: f(x) = |x|

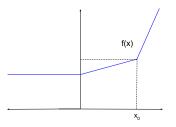
Challenge: Find "derivative" of f(x) = |x| at x = 0



Non-differentiable function at x = 0

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Non-differentiable function at x = 0

Classical calculus: Derivative doesn't exist at x = 0Subgradient calculus: We can find a set of valid subgradients!

Pop Quiz: Subgradient Intuition

Quick Quiz 1

For f(x) = |x| at x = 0, which values could be subgradients?

a) Only g = 0

Answer: b) Any value in [-1,1] satisfies the subgradient condition!

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- b) Any $g \in [-1, 1]$
- c) Only g = 1 or g = -1

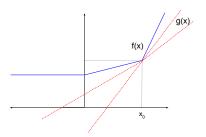
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- Construct a differentiable g(x)

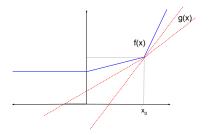
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 - Below or on f(x) for all x



• Compute slope of g(x) at $x = x_0$



Another Example: f(x) = |x|

• Subgradient of f(x) belongs to [-1,1]

